MixPoet: Diverse Poetry Generation via Learning Controllable Mixed Latent Space
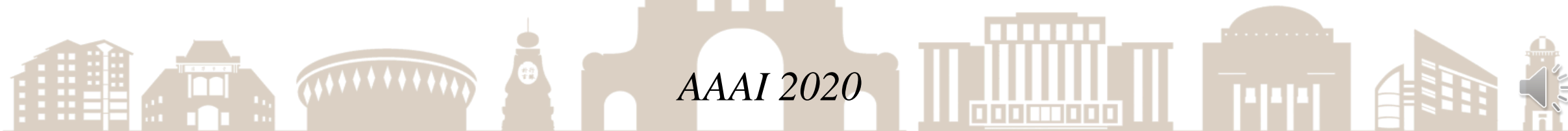
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AAAI 2020

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Poetry

✓Elegant Expressions

✓Colorful Contents

✓Diverse Styles
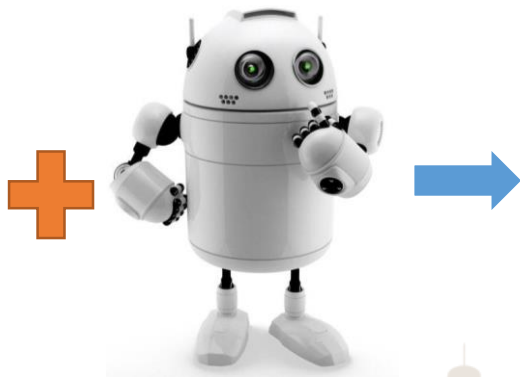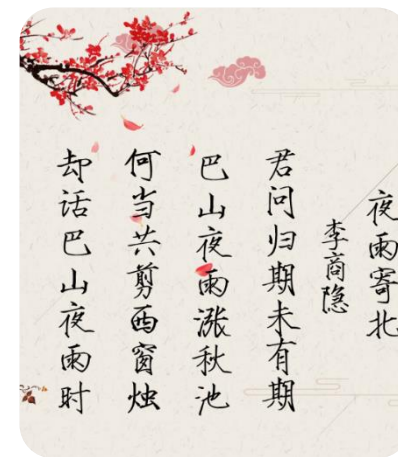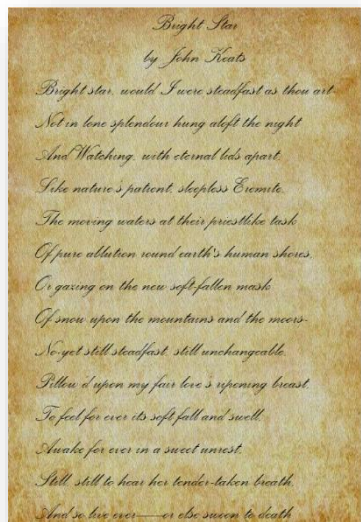
Exploration
- Human Writing Mechanism
- Computational Creativity
- Humanizing AI

Application
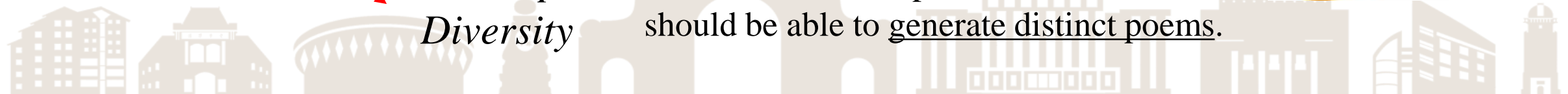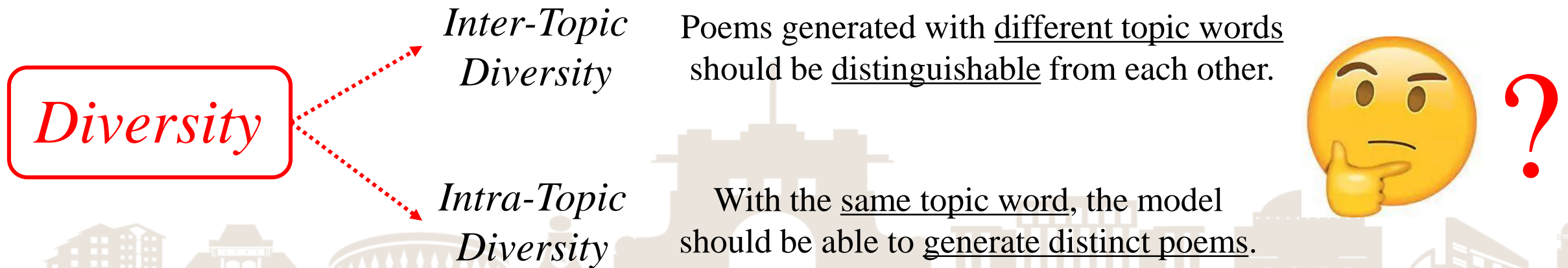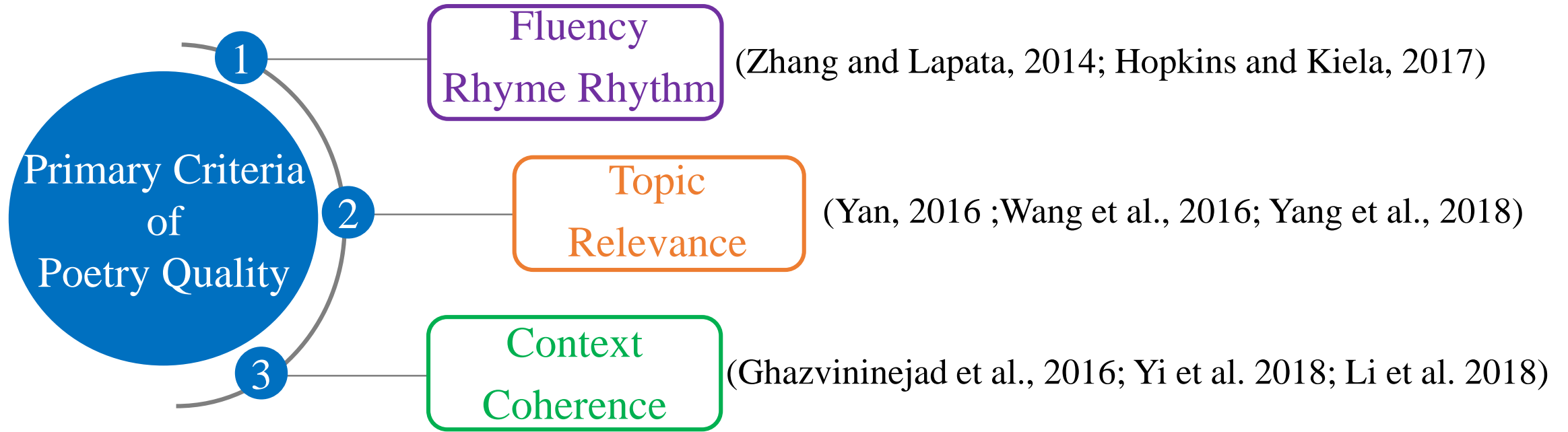- Entertainments
- Advertising
- Poetry Education
- Literary Research

...

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Primary Criteria of Poetry Quality

1. **Fluency Rhyme Rhythm** — (Zhang and Lapata, 2014; Hopkins and Kiela, 2017)

2. **Topic Relevance** — (Yan, 2016 ; Wang et al., 2016; Yang et al., 2018)

3. **Context Coherence** — (Ghazvininejad et al., 2016; Yi et al. 2018; Li et al. 2018)

Diversity

Inter-Topic Diversity Poems generated with <u>different topic words</u> should be <u>distinguishable</u> from each other.

Intra-Topic Diversity With the <u>same topic word</u>, the model should be able to <u>generate distinct poems</u>.
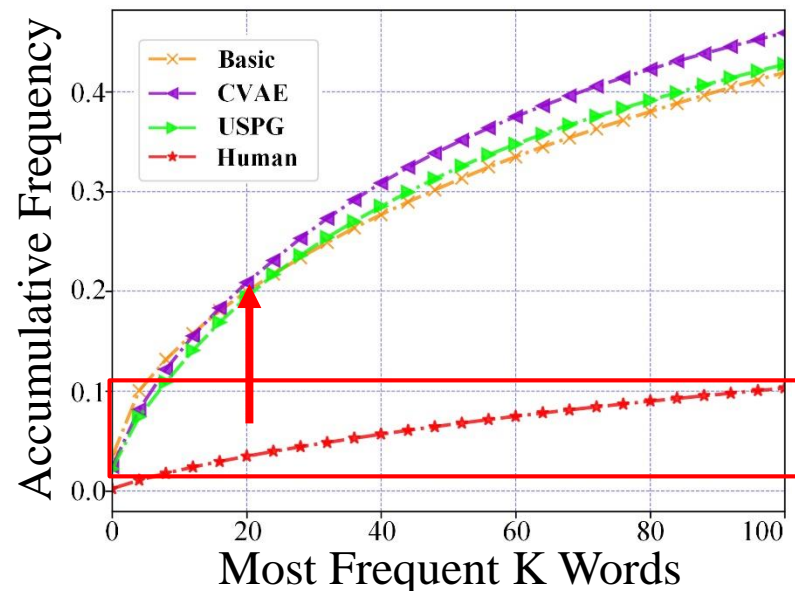
Existing models tend to
- remember common patterns in the corpus
- produce repetitive and generic contents

The most frequent 20 words account for 20% of all generated contents!

Input keyword：desolation

萧条风雨夜，
I see desolation on a stormy night.
寂寞夕阳边。
I feel lonely at sunset.
何处堪惆怅，
Where can I place my sadness?
无人问钓船。
No one cares about the fishing
ship's course.

Input keyword：autumn lake

山中秋水阔，
In autumn, the lake in the mountains
becomes broad.
门外夕阳斜。
Through the door, I see the sunset.
何处堪惆怅，
Where can I place my sadness?
西风起暮鸦。
At dusk, along with the westerly
wind, crows start to dance.

Distinct input keywords

- Repetitive words
- Identical lines

Human-authored poems are highly diverse!

Each human poet has his/her own styles.

One possible solution: modeling each individual poet. 🤔
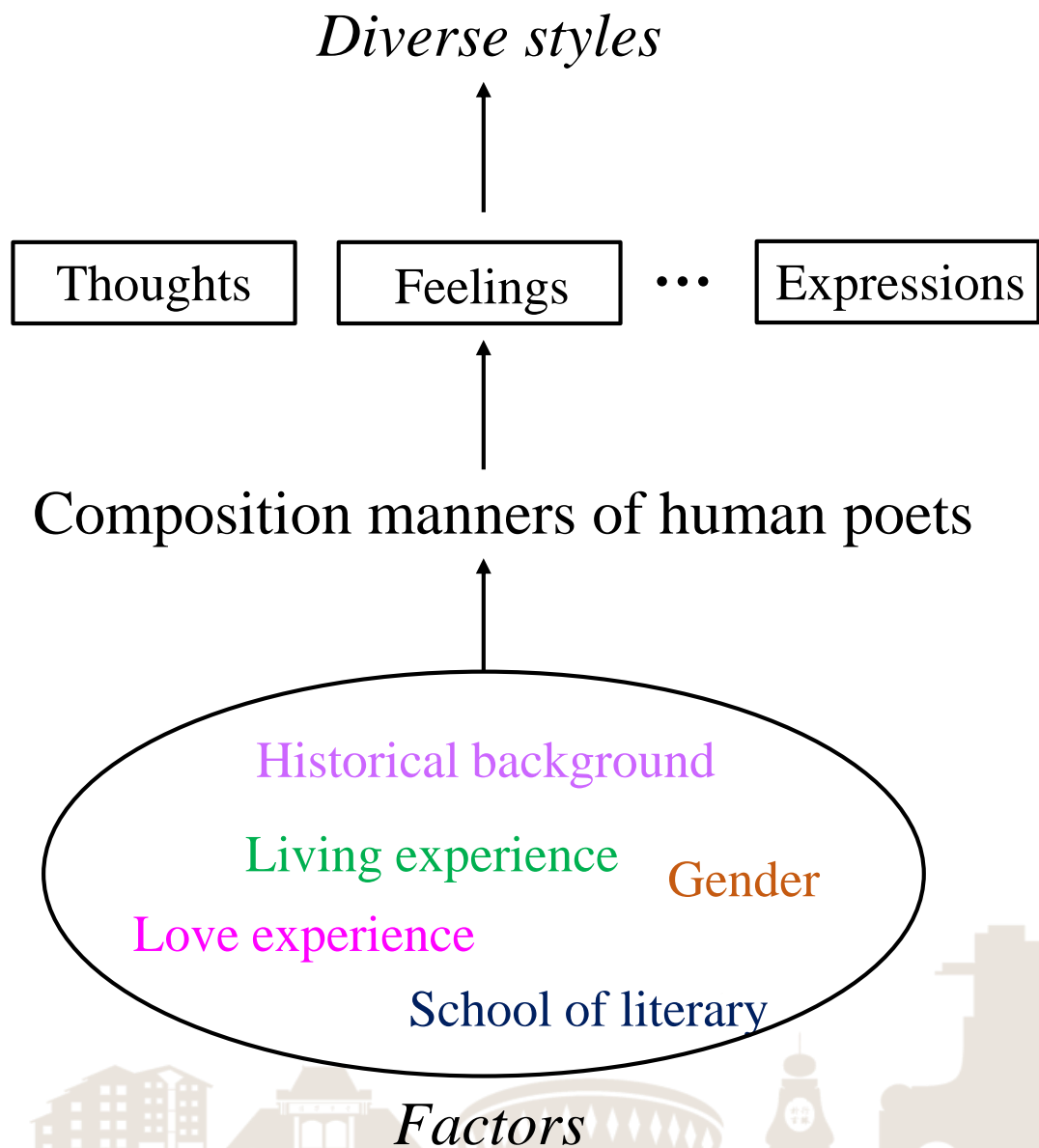(Wei et al., 2018; Tikhonov and Yamshchikov, 2018)

- Sparsity of data 😔

- Inconsistency of a poet's style 😔

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Diverse styles

| Thoughts | | Feelings | ⋯ | Expressions |

Composition manners of human poets

Factors

Historical background

Living experience

Gender

Love experience

School of literary

塞上长城空自许，镜中衰鬓已先斑。
陆游 南宋 《书愤五首·其一》

黄沙百战穿金甲,不破楼兰终不还
王昌龄 盛唐 《从军行七首·其四》
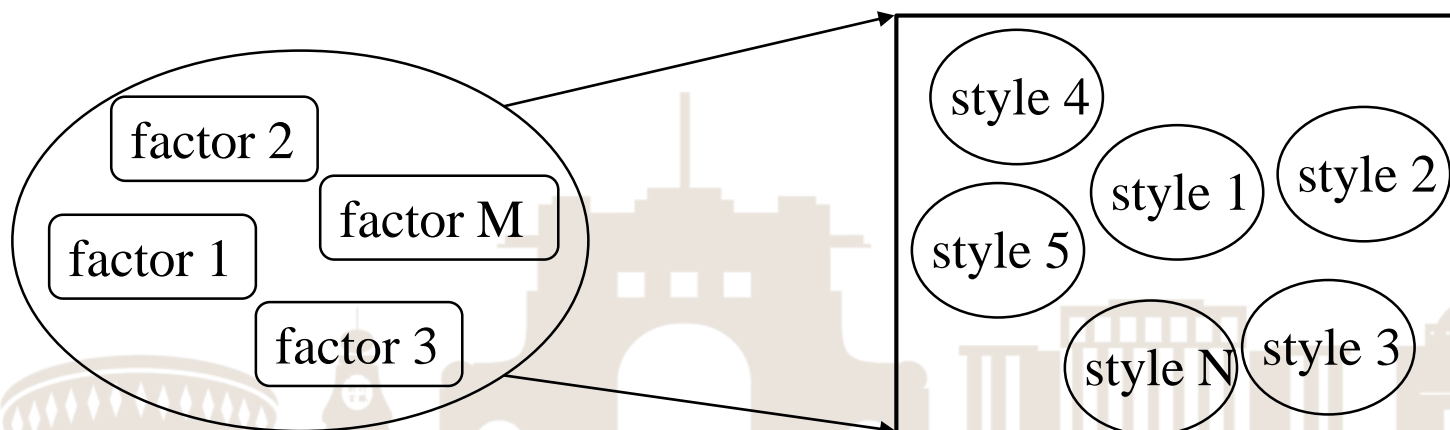
人闲桂花落，夜静春山空。
王维 《鸟鸣涧》

孤城向水闭,独鸟背人飞。
刘长卿 《馀干旅舍》

Model each individual poet. 😔

Model each influence factor! 😄

- Gather poems that share the same factor value   ~~Sparse data~~

- Focus on the characteristics of each poem   ~~Changeable styles of one poet~~
       instead of each poet

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➢ Overview

M factors $y_1, \ldots, y_i, \ldots, y_M$
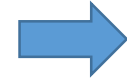
Each factor y_i is discretized into K_i classes

$$\prod_{i=1}^{m} K_i \quad \text{factor mixtures}$$

New distinctive styles!

$$p(x, y|w) = \int_z p(x, y, z|w)\, dz$$

x poem

w user-specified keyword

z latent variable

     to capture factor-related properties

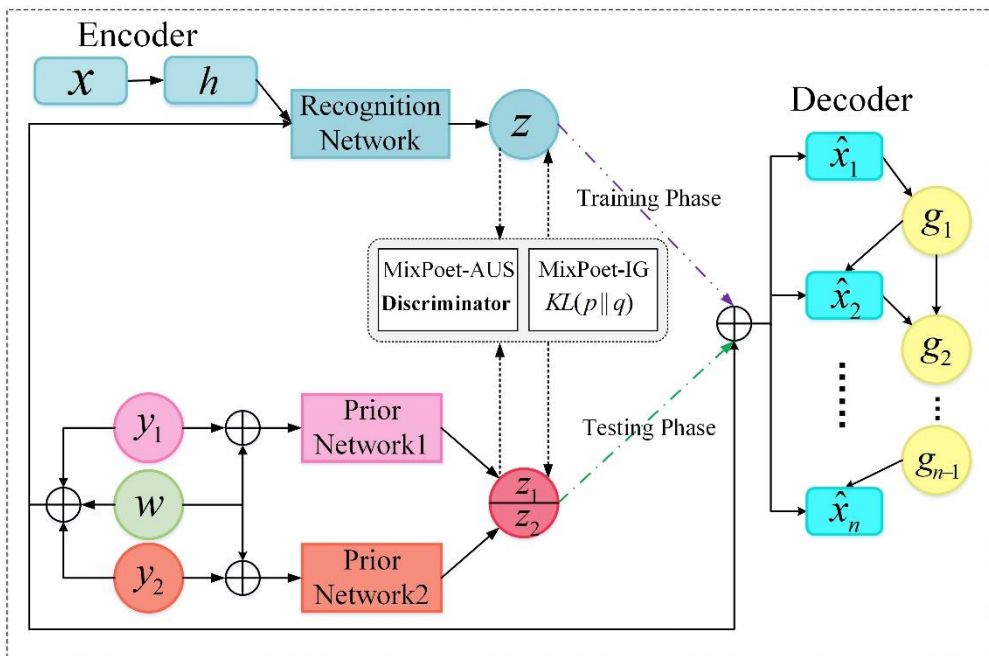$$p(x, y, z|w) = p(y|w) * p(z|w, y) * p(x|w, y, z)$$

latent space !

Previous work:
$[z; y]$ (Hu et al., 2017)

• Poetry style is tightly coupled with semantics! (Embler,1967)

• Interpretability & controllability

Overview
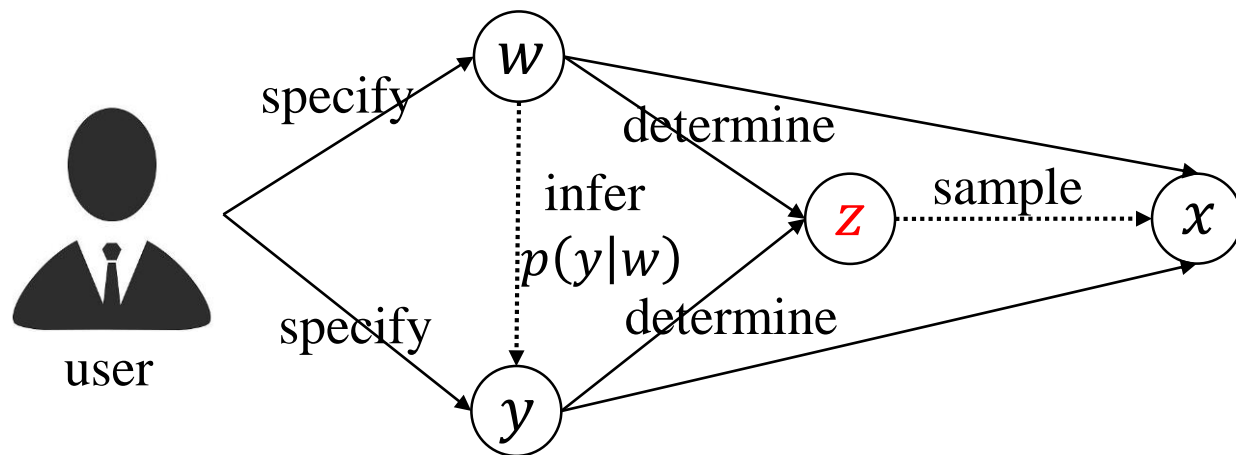
Figure1: A graphical illustration of MixPoet

$$p(x, y, z|w) = p(y|w) * p(z|w, y) * p(x|w, y, z)$$

w + different mixtures of y_i ⟶ *intra-topic diversity* √

different w + inferred y_i ⟶ *inter-topic diversity* √

➤ Semi-Supervised Conditional VAE

☐ For labelled data

$$\log p(x, y|w) \geq -L(x, y, w)$$

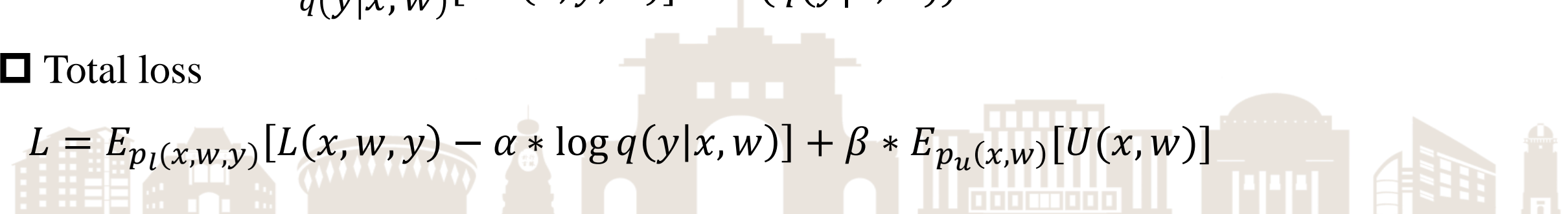$$= E_{q(z|x, w, y)}[\log p(x|z, w, y)] - KL[q(z|x, w, y)||p(z|w, y)] + \log p(y|w)$$

Prior Network

Decoder

Recognition Network

Classifier

☐ For unlabelled data (following (Kingma et al. 2014))

$$\log p(x|w) \geq -U(x, w)$$

$$= E_{q(y|x, w)}[-L(x, y, w)] + H(q(y|x, w))$$

Classifier

☐ Total loss

$$L = E_{p_l(x, w, y)}[L(x, w, y) - \alpha * \log q(y|x, w)] + \beta * E_{p_u(x, w)}[U(x, w)]$$
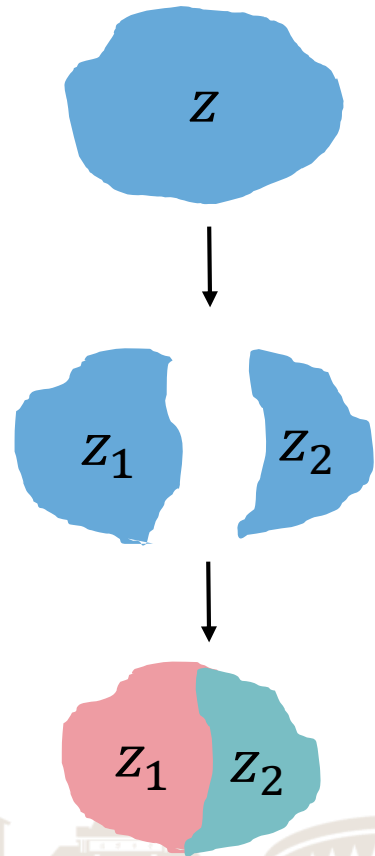
➤ Latent Space Mixture

To incorporate multiple factors $\quad z = [z_1, z_2, \ldots, z_M]$

e.g., $M = 2$

Assume:

(1) independence of influence factors y_1, y_2

(2) conditional independence of subspaces z_1, z_2

$$p(z|w, y) = p(z_1|w, y_1)p(z_2|w, y_2)$$

Independently specify the values of different factor

A latent space which mixes the properties of multiple factors!

➢ (1) Mixture for Isotropic Gaussian Space (MixPoet-IG)

Assume $z \sim N(\mu, \sigma^2 I)$ ➡ $KL[q(z|x,w,y)||p(z|w,y)]$

$$= KL[q(z_1|x,w,y_1)||p(z_1|w,y_1)]$$
$$+KL[q(z_2|x,w,y_2)||p(z_2|w,y_2)]$$

Analytically minimize these two KL terms!

Independent dimensions of the latent variable ➡ Not expressive enough 😔

(Dilokthanakul et al. 2017)

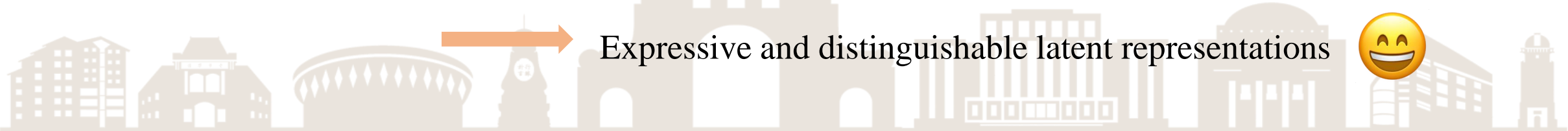A complex latent space with

(1) independent subspaces (z_1, z_2)

➡ Independent control of each factor 😄

(2) entangled internal dimensions of each subspace
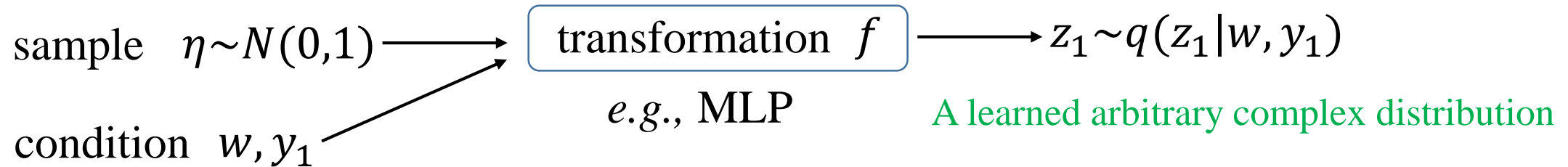
➡ Expressive and distinguishable latent representations 😄

> ➤ (2) Adversarial Mixture for Universal Space (MixPoet-AUS)

Universal Approximator (Makhzani et al. 2015)

$$q(z|c,\eta) = \delta(z - f(c,\eta)) \quad \eta \sim N(0,1)$$

condition   simple distribution

sample $\eta \sim N(0,1)$ ⟶ transformation f ⟶ $z_1 \sim q(z_1|w,y_1)$

condition w, y_1 $e.g.,$ MLP   A learned arbitrary complex distribution

Independent samples of z_1, z_2 from learned arbitrary complex distributions!   get√

➢ (2) Adversarial Mixture for Universal Space (MixPoet-AUS)

$KL[q(z|x,w,y)||p(z|w,y)]$ No analytical form!

Density Ratio Loss (Rosca et al. 2017)

$$KL[q(z|x,w,y_1,y_2)||p(z_1|w,y_1)p(z_2|w,y_2)]$$

$$= E_{q(z|x,w,y_1,y_2)}[\log \frac{q(z|x,w,y_1,y_2)}{p(z_1|w,y_1)p(z_2|w,y_2)}]$$

Conditional latent discriminator

$$\approx E_{q(z|x,w,y_1,y_2)}[\log \frac{C(z,y_1,y_2)}{1-C([z_1;z_2],y_1,y_2)}]$$

➤ (2) Adversarial Mixture for Universal Space (MixPoet-AUS)

$$z \sim q(z|x, w, y_1, y_2) \longrightarrow z$$

$$z_1 \sim q(z_1|w, y_1) \longrightarrow z_1$$

$$z_2 \sim q(z_2|w, y_2) \longrightarrow z_2$$

$$\longrightarrow \frac{z_1}{z_2}$$
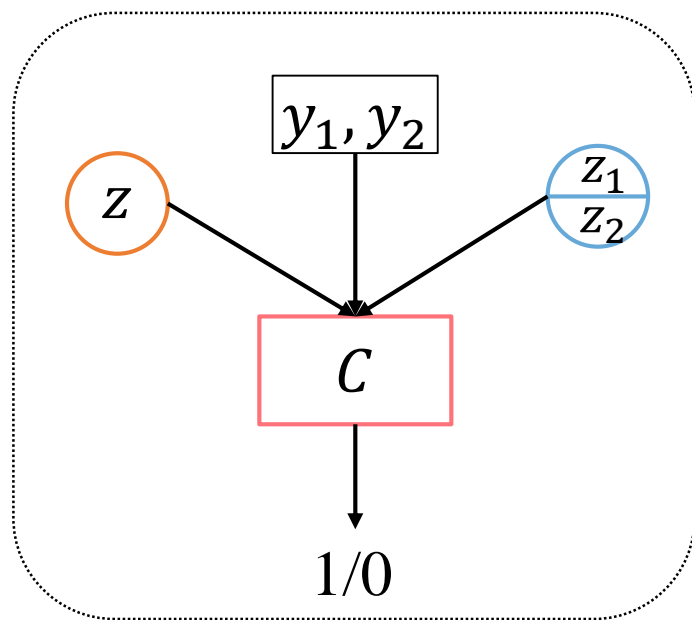
When the discriminator is cheated

$$C(\cdot) \approx 0.5$$

$$KL[q(z|x, w, y_1, y_2) || p(z_1|w, y_1)p(z_2|w, y_2)] \approx 0$$

y_1, y_2

z

$\frac{z_1}{z_2}$

C

1/0

Use adversarial training to minimize the ratio loss

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➤ Dataset

Military Career (MC)

Living Experience ⟶ Countryside Life (CL)
(Dilthey 1985)

Two typical factors   Others   ⟶ 3 ∗ 2 = 6 styles!

Troubled Times (TT)

Historical Background ⟶
(Owen 1990)   Prosperous Times (PT)
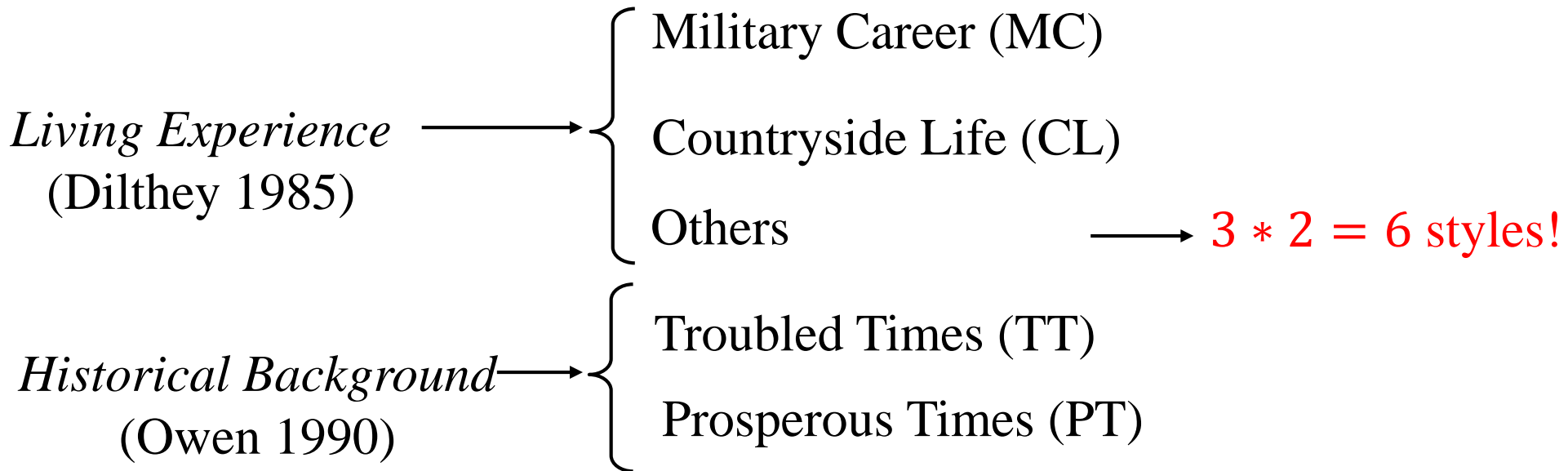
# of	MC	CL	Others	UNK	Total
PT	799	608	675	9,052	11,134
TT	1,481	977	1,122	8,993	12,573
UNK	8,547	9,543	7,654	-	25,744
Total	10,827	11,128	9,451	18,045	49,451

Table 1: Statistics of labelled poems.

- 49,451 labelled poems

- 117k unlabelled poems

➤ Experiment Results

Models	inter-JS ↓	intra-JS ↓
fBasic	-	9.15%
Basic	2.58%	-
CVAE	2.34%	38.2%
USPG	1.89%	5.01%
MRL	**1.28%**	-
MixPoet-IG	1.55%	8.35%
MixPoet-AUS	1.39%	**3.73%**
GT	0.12%	-

Table 2: Automatic evaluation results of diversity.

Figure 2: Factor control accuracy.
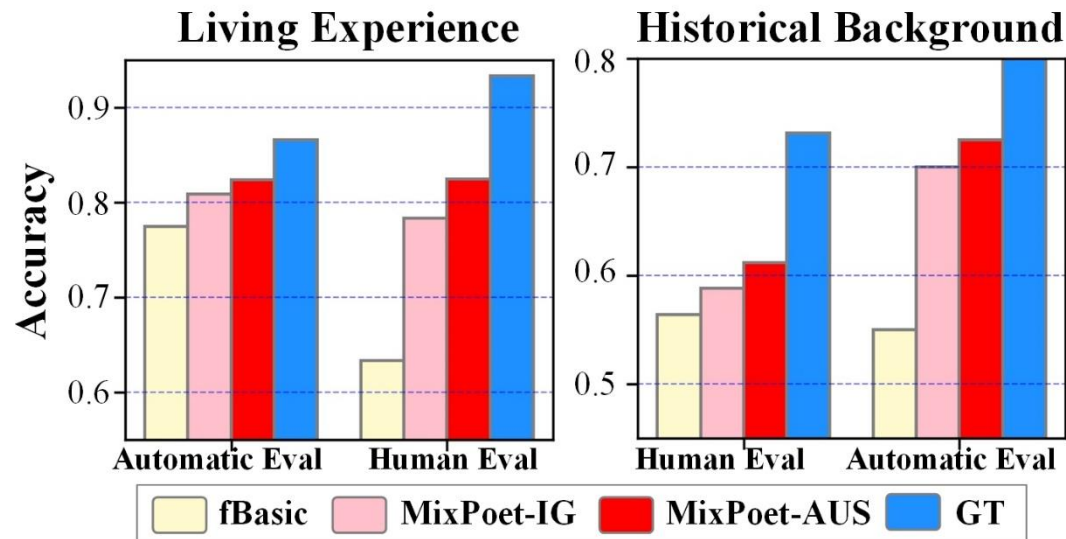
controllable to some extent!

Models	Fluency	Coherence	Meaning	Aesthetics	Relevance	Overall Quality
Basic	3.00	2.54	2.30	2.71	2.54	2.35
USPG	3.09	2.65	2.61	2.98	2.73	2.63
CVAE	3.34	2.78	2.64	3.13	2.70	2.81
MRL	3.91	3.66	3.36	3.73	3.19	3.55
MixPoet	**4.18**[**]	**4.10**[**]	**3.75**[**]	**4.10**[**]	**3.39**	**3.98**[**]
GT	4.25	4.36[+]	4.19[++]	4.20	3.99[++]	4.25[+]

Table 3: Human evaluation results of quality.

➤ Analysis
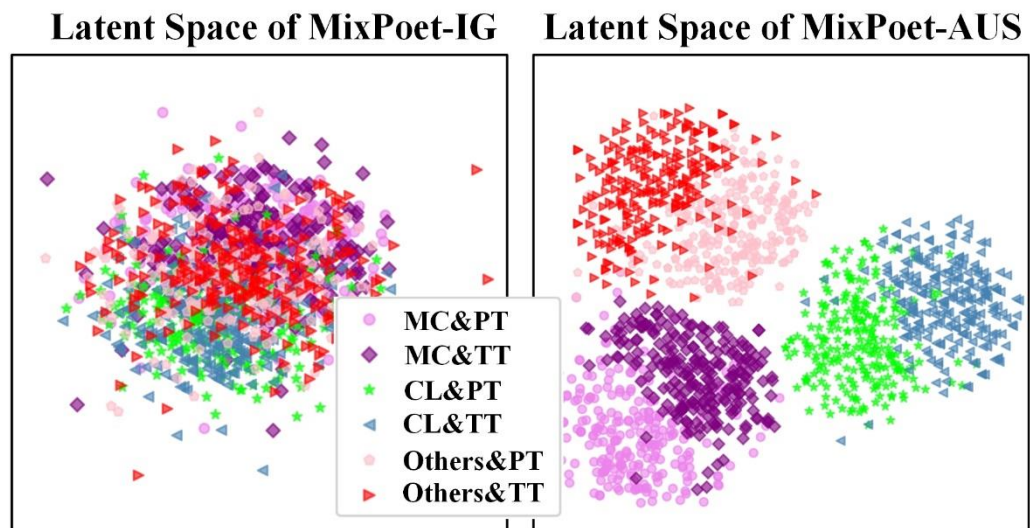
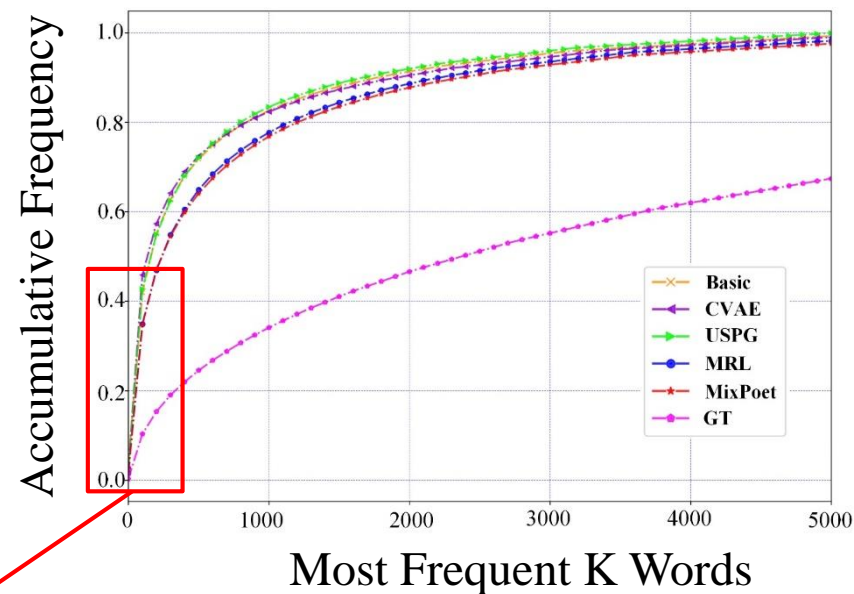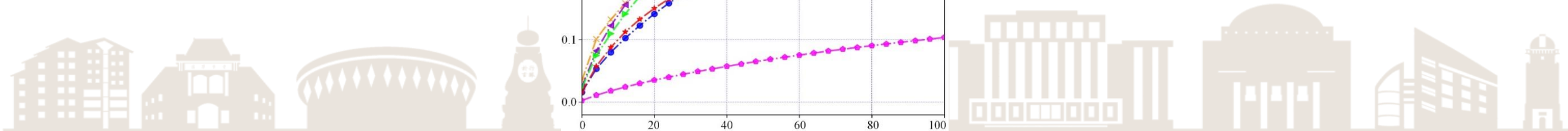Figure 4 (a): Visualization of samples of z conditioned on the keyword 'spring wind' and different mixtures.

Figure 4 (b): Accumulative frequency of the most frequent k words in generated poems.

➢ Case Study

Figure 5: Poems generated by baseline Basic (a), USPG (b) and MixPoet with different mixtures (c, d). Repetitive phrases are marked in red. Phrases meeting different factor classes are marked in corresponding colors.

➤ General Comparison

Models	Inter-topic diversity	Intra-topic diversity	Main contributor to diversity	Interpretability of styles
CVAE (Yang et al., 2018a)	√	√	Randomness resulted by different samples from the latent space.	✗
MRL (Yi et al., 2018)	√√√√	✗	Encourage the generation of high-TF-IDF words.	✗
USPG (Yang et al., 2018b)	√√	√√	Disentangle poetry space into different clusters	✗
MixPoet (Ours)	√√√	√√√	Mix different influence factors conditioned latent subspaces.	Different factor mixture

MixPoet {
- Best intra-topic diversity
- Satisfactory inter-topic diversity
- Interpretable and distinguishable styles

➢ Conclusion

- A novel poetry generation model – *MixPoet*
  - Semi-supervised structure
  - Absorb and mix multiple factors which influence human poetry composition.
  - Controllability of factor-related properties
  - More distinguishable latent space
  - Improve both intra-topic & inter-topic diversity

- Future Work
  - More factors, *e.g.*, love experience, school of literary, gender, and age
  - Finer-granularity discretization, *e.g.*, more classes for each factor (even continuous values?)
  - Dependence of influence factors, *e.g.*, living experience is related to gender

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Jiuge （九歌）

A Chinese poetry generation system developed by THUNLP lab.

- Support most popular genres of Chinese poetry
- Multi-style choices
- Human-machine collaborative creation
- Automatic Recommendation of related human-authored poems.
- Page View > 7 million

Jiuge（九歌）

Online system: https://jiuge.thunlp.cn/

Github: https://github.com/thunlp-aipoet

Source codes and data and of Jiuge systems will be gradually released via our github page!

Thanks!

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Any questions or suggestions, please feel free to email us!